

State-of-charge estimation of valve regulated lead acid battery based on multi-state Unscented Kalman Filter

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ABSTRACT

As a vital part of the battery-employed system, battery management system (BMS) must correctly estimate values descriptive of the battery's present operating condition. As is known to all, state-of-charge (SOC) is a key battery state for BMS to estimate. In this paper, based on Unscented Kalman Filter (UKF) theory and a comprehensive battery model, a novel SOC estimation method is proposed. A nonlinear mapping process is involved to recursively calculate the system state variable, thus the errors caused by Extended Kalman Filter (EKF) can be effectively restrained; besides, compared with many simple battery models recently, the comprehensive model presented in this paper can track the operating performance of valve regulated lead acid (VRLA) battery more correctly. The whole estimation process is clearly given; then EKF and UKF are compared through experimental analysis; the results show that UKF method is superior to EKF method in SOC estimation for VRLA battery.

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1. Introduction

Due to the energy crisis and globally increasing pollution problems, more and more countries have attached great importance to the research and development of renewable and clean energy sources. In such a case, storage battery is regarded as one of the most promising solutions. However, the nonlinear dynamic performance of the battery makes it difficult to monitor the operating states. Without a doubt, SOC is a key battery state to estimate, so SOC estimation is a popular research area now.

There are several common techniques recently for SOC estimation: Ah counting based on current integration; open-circuit voltage (OCV) method and electromotive force (EMF) method based on battery terminal voltage detection; neural network method based on massive sample data; Kalman Filter based on state space model; and some other methods based on chemical process analysis [1–4]. The UKF theory adopted here belongs to Kalman Filter family.

Kalman Filter is a powerful state estimation technique for dynamic system. It can give an optimal estimate of the system state with minimum error covariance. But when the system is nonlinear, then a linearization process needs to be done to approximate the real system, and this is the very concept of the EKF method. However, EKF also brings some other problems like linearization error and complicated computation of Jacobian matrix,

so it is difficult to assure the estimation accuracy especially in the high nonlinear systems and the total cost is increased by powerful processor due to the intensive computation; besides, it has to be taken into consideration that EKF requires a precise model of cell dynamics, which changes as the battery ages, also EKF performance is poor in transients [5,6]. In order to get rid of these defects, Julier and Uhlmann proposed a nonlinear filter called UKF in 1990s. Unlike the EKF, UKF adopts a nonlinear unscented transformation (UT) and approximates a Gaussian distribution of the state random variable. It only needs a set of sample points that are refreshed at each time step, in this way the posterior mean and covariance can be recursively transmitted according to the nonlinear mapping, and at the same time Jacobian computation can also be avoided [7].

In this paper, UKF method is adopted in SOC estimation process combining with a comprehensive VRLA battery model. Unlike the commonly used empirical equation model described in [8], the battery model presented here takes an auxiliary state into account besides SOC state. As a result, the EMF method and Ah counting method are closely organized through UKF algorithm to form the final SOC estimator.

2. Comprehensive battery model

Thevenin model is a widely employed battery model, it can simulate the battery behavior well; and it is a first-order system [9–11]. So it is adopted here as part of our comprehensive model, shown in Fig. 1. R_1 is an ohm resistance, R_2 is a polarized resistance, C is an equivalent capacitor, V is OCV or terminal voltage,

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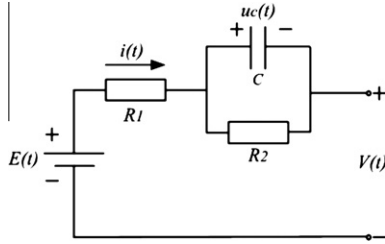


Fig. 1. Thevenin model.

and E stands for the EMF (after resting for over 3 h, basically OCV will equal to EMF of the battery). This Thevenin model is basis of EMF method.

Analyze this Thevenin model, we easily have:

$$E(t) = V(t) + R_1 i(t) + u_c(t) \quad (1)$$

$$i(t) = \frac{u_c(t)}{R_2} + C \frac{du_c}{dt} \quad (2)$$

According to EMF concept, a nonlinear relationship between EMF and SOC can be expressed as:

$$E(t) = F[S(t)] + \Delta E(T) \quad (3)$$

In Eq. (3) above, $S(t)$ is the battery SOC at time t , $F[S(t)]$ is a nonlinear function of SOC, this function is extracted from a mass of experimental data, we have described the further details of this EMF method in another paper [12]; and $\Delta E(T)$ stands for the increment of EMF when temperature is changing, because all of the experiments are implemented under room temperature around 20–25 °C, also the battery temperature does not change obviously, here we assume $\Delta E(T) = 0$.

Besides, battery performance could also be expressed through an Ah counting model:

$$S(t) = S(t_0) + \int_{t_0}^t \frac{k_i k_T i(t)}{k_i Q_0} dt \quad (4)$$

In Eq. (4), Q_0 is the rated capacity; k_i , k_T and k_l are the three compensation factors related to working current, temperature and battery state of health (SOH) respectively. The three factors are determined as follows: k_i equals to the ratio of actual battery capacity to the charge quantity that could be taken out of a battery under different C-rates, with the help of Matlab fitting tool, a relationship between the working current and k_i can be extracted; ignoring the influence of temperature, we let $k_T = 1$; k_l is the ratio of actual available capacity to the rated capacity of the battery.

Combining the EMF method and Ah model, a comprehensive battery model easy to realize UKF algorithm could be established according to Eqs. (1)–(4):

$$\begin{bmatrix} S(k+1) \\ u_c(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \exp\left(-\frac{T}{R_2 C}\right) \end{bmatrix} \begin{bmatrix} S(k) \\ u_c(k) \end{bmatrix} + \begin{bmatrix} -\frac{k_i k_T T}{k_i Q_0} \\ R_2 \left(1 - \exp\left(-\frac{T}{R_2 C}\right)\right) \end{bmatrix} i(k) + \begin{bmatrix} w_s(k) \\ w_{uc}(k) \end{bmatrix} \quad (5)$$

$$V(k) = F[S(k)] - u_c(k) - R_1 i(k) + \Delta E(T) + v(k) \quad (6)$$

In this model, the input is working current $i(k)$, and output is the battery terminal voltage $V(k)$. In addition to the state $S(k)$, the voltage of equivalent capacitor $u_c(k)$ is taken into consideration as an auxiliary state. The model noise is $w(k) = [w_s(k), w_{uc}(k)]^T$, and measurement noise is $v(k)$, both $w(k)$ and $v(k)$ are assumed to be mutually uncorrelated white Gaussian random processes with zero mean.

3. Application of multi-state UKF in SOC estimation

According to the concept of UKF, Eqs. (5) and (6) are system state equation and measurement equation respectively. Next, the new state variable is redefined as:

$$X(k) = [x(k)^T, w(k)^T, v(k)^T]^T = [S(k), u_c(k), w_s(k), w_{uc}(k), v(k)]^T \quad (7)$$

In this way, an extension of the state variable is realized, and dimension of the new state variable is 5, its mean value is $\bar{X}$ and its variance is P^X . Firstly we choose N sample points with their weight factors: $S = \{\omega_i, \chi_i; i = 0, 1, 2, \dots, 10\}$, where $N = 2L + 1$ and L is state variable dimension, so here $N = 11$. χ_i is the one of the chosen sample points and ω_i is its weight factor, the points are chosen under the following rules:

$$\begin{cases} \chi_0 = \bar{X}; i = 0 \\ \chi_i = \bar{X} + (\sqrt{(L+\lambda)P^X})_i; i = 1, 2, \dots, 5 \\ \chi_i = \bar{X} - (\sqrt{(L+\lambda)P^X})_{i-5}; i = 6, 7, \dots, 10 \end{cases} \quad (8)$$

$$\begin{cases} \omega_0^{(m)} = \lambda / (L + \lambda) \\ \omega_0^{(c)} = \lambda / (L + \lambda) + (1 - \alpha^2 + \beta) \\ \omega_i^{(m)} = \omega_i^{(c)} = 1 / \{2(L + \lambda)\}; i = 1, 2, \dots, 10 \end{cases} \quad (9)$$

where λ is a composite coefficient and it should satisfy the following equation:

$$\lambda = \alpha^2 (L + K) - L \quad (10)$$

In Eqs. (8)–(10), $\omega^{(m)}$ is the weight factor of sample point mean value and $\omega^{(c)}$ is the weight factor of sample point variance; and $(\sqrt{(L+\lambda)P^X})_i$ is the i th column of matrix $\sqrt{(L+\lambda)P^X}$; parameter K need to satisfy $K \geq 0$, here we assume $K = 0$; α is new sigma point scaling parameter, which determines the spread of points around $\bar{X}$, the relation $0 \leq \alpha \leq 1$ should be met, here we let $\alpha = 1$; β is used to take account of prior knowledge on the distribution of X , and $\beta = 2$ is the optimal choice for Gaussian distributions. Next, the whole SOC estimation process is clearly given step by step:

Step 1: Initialize the mean value and variance of system states.

According to the new state variable in Eq. (7), we get:

$$\bar{X}(0) = E[X(0)] = [E[S(0)], E[u_c(0)], 0, 0, 0]^T \quad (11)$$

$$P^X(0) = \begin{bmatrix} P^X(0) & 0 & 0 \\ 0 & Q & 0 \\ 0 & 0 & R \end{bmatrix} \quad (12)$$

$\bar{X}(0)$ is the initial mean value of the new state variable, P^X in Eq. (12) is variance matrix of the primitive state variable $x(k) = [S(k), u_c(k)]^T$, Q and R are the variance matrixes of model noise and measurement noise respectively. So P^X is actually a matrix of 5×5 .

Step 2: Calculate the sample points and their weight factors.

In case that $\bar{X}(k-1)$ and $P^X(k-1)$ are known, then χ_i , $\omega_i^{(m)}$ and $\omega_i^{(c)}$ ($i = 0, 1 \dots 10$) can be calculated through Eqs. (8)–(10).

Step 3: Refresh sample points and estimate system states.

Firstly each sample point is refreshed through Eq. (5), in this way a group of 11 new points can be obtained: $\chi_i(k|k-1)$, $i = 0, 1 \dots 10$. Then the mean value and covariance of the system state variable is estimated through Eqs. (13) and (14):

$$\bar{X}(k|k-1) = \sum_{i=0}^{10} \omega_i^{(m)} \chi_i(k|k-1) \quad (13)$$

$$P^{\bar{X}}(k) = \sum_{i=0}^{10} \omega_i^{(c)} [\chi_i(k|k-1) - \bar{X}(k|k-1)][\chi_i(k|k-1) - \bar{X}(k|k-1)]^T \quad (14)$$

Step 4: Estimate system output.

In this step, firstly the output variable corresponding to each refreshed sample point is estimated:

$$y_i(k|k-1) = F[S_i(k)] - u_{c,i}(k) - R_1 i(k) + \Delta E(T) + v_i(k) \quad (15)$$

Note that the relationship between EMF and SOC expressed as $F[S(k)]$ is nonlinear, so Eq. (15) is a nonlinear mapping process. $S_i(k)$, $u_{c,i}(k)$ and $v_i(k)$ are the elements of each sample point, where $i = 0, 1 \dots 10$. Next, mean value and covariance of the system output is estimated through Eqs. (16) and (17):

$$\bar{Y}(k|k-1) = \sum_{i=0}^{10} \omega_i^{(m)} y_i(k|k-1) \quad (16)$$

$$P^{\bar{Y}}(k) = \sum_{i=0}^{10} \omega_i^{(c)} [y_i(k|k-1) - \bar{Y}(k|k-1)][y_i(k|k-1) - \bar{Y}(k|k-1)]^T \quad (17)$$

Step 5: Calculate UKF gain matrix and refresh system state variable.

Firstly the covariance of system state and output is calculated:

$$P^{XY}(k) = \sum_{i=0}^{10} \omega_i^{(c)} [\chi_i(k|k-1) - \bar{X}(k|k-1)][y_i(k|k-1) - \bar{Y}(k|k-1)]^T \quad (18)$$

Then UKF gain matrix is obtained, mean value and variance of system state is refreshed:

$$K(k) = P^{XY}(k)P^{\bar{Y}}(k)^{-1} \quad (19)$$

$$\bar{X}(k) = \bar{X}(k|k-1) + K(k)[Y(k) - \bar{Y}(k|k-1)] \quad (20)$$

$$P^{\bar{X}}(k) = P^{\bar{X}}(k) - K(k)P^{\bar{Y}}(k)K(k)^T \quad (21)$$

In Eq. (20), $Y(k)$ is the actual terminal voltage of the battery. After step 5, it goes to step 2 to complete the whole recursive process.

Analyzing all the steps above, the core concept of this SOC estimation strategy could be clearly seen: first, an estimated value of the battery terminal voltage is obtained according to EMF method by using the initial value of SOC and equivalent capacitor voltage; and then compare the estimated terminal voltage with the measured battery terminal voltage, the difference of the two is used to calculate the UKF gain matrix and refresh system state; finally, a new round of recurrence is started according to the refreshed system state. So battery SOC estimated by this method is not merely calculated by Ah counting, it also involves EMF concept.

4. Experiment and analysis

The first set of experiments are performed using 46B24LS-MFZ 12 V/45Ah VRLA battery with its actual available capacity of about 40Ah; the voltage and current value are measured by our self-developed data collection board based on TI DSP 2407; all of these experimental data are transmitted to PC, and recorded each second with the help of a BMS monitoring tool; both UKF method presented in this paper and commonly used EKF method are applied

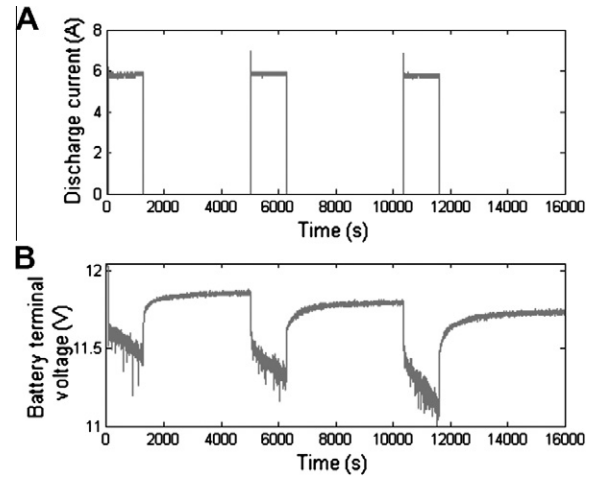


Fig. 2. Discharge current and battery terminal voltage under constant current pulse discharge test.

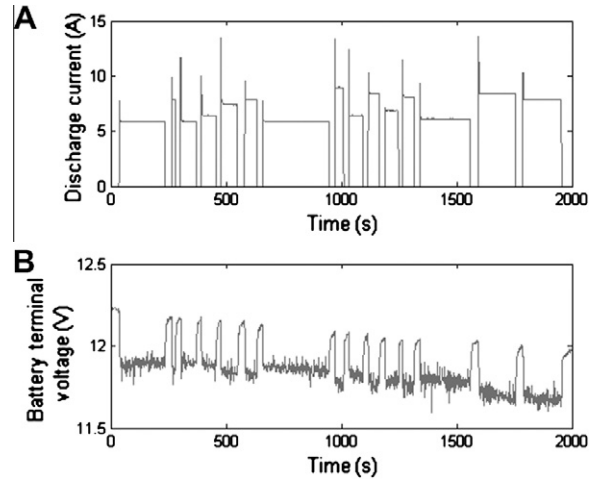


Fig. 3. Discharge current and battery terminal voltage under random current pulse discharge test.

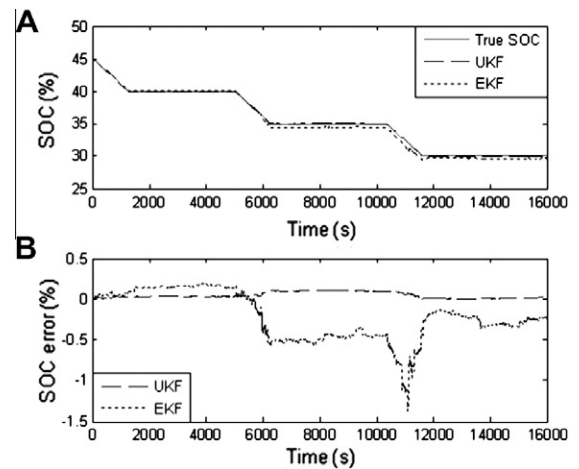


Fig. 4. Comparison of SOC curves under constant current pulse discharge test.

to estimate the battery SOC, the results are compared and analyzed.

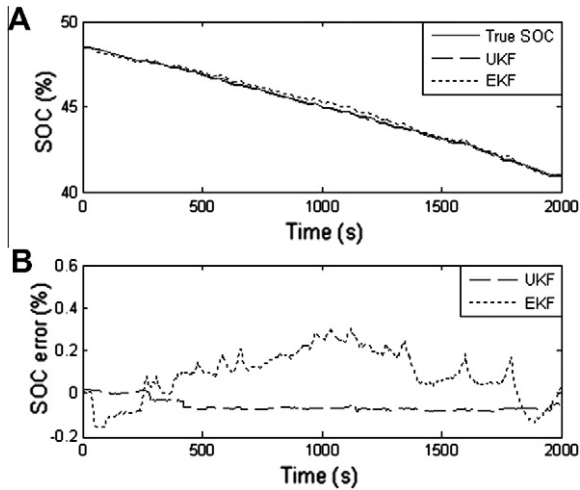


Fig. 5. Comparison of SOC curves under random current pulse discharge test.

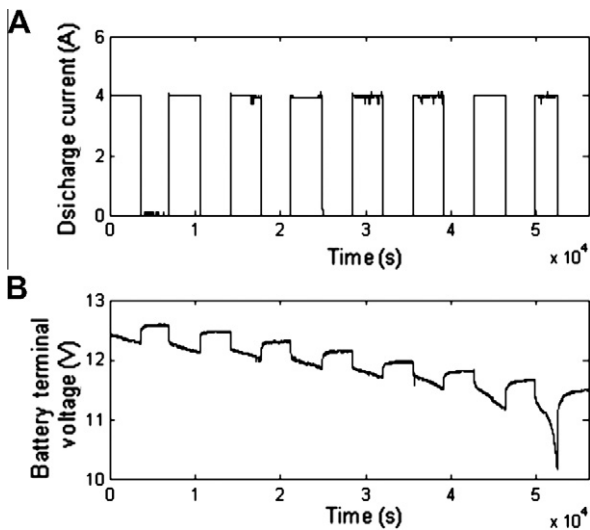


Fig. 6. Discharge current and battery terminal voltage under constant current pulse discharge test.

Primitive experimental data are shown in Figs. 2 and 3. Fig. 2 shows the current and terminal voltage of a constant current pulse discharge test, Fig. 3 shows the current and terminal voltage of a random current pulse discharge test.

Both EKF method and UKF method are applied to estimate SOC under the same experiment and the same related parameters. Results are shown as follows:

Comparison of SOC curves estimated under constant current pulse discharge test are shown in Fig. 4, the initial SOC value is determined as 45% by EMF method before the discharge test is started, and the initial value of equivalent capacitor voltage is 0 V. SOC curves estimated by EKF and UKF are compared with the true value. It is obvious that the error caused by our UKF method is much smaller than the error caused by EKF method, the maximum SOC error of UKF method is about 0.12%, while maximum error caused by EKF is larger than 1%. Similarly, comparison of SOC curves estimated under random current pulse discharge test are shown in Fig. 5, the maximum error occurred in UKF method is only 0.08%, while maximum error caused by EKF is up to 0.3%. So, SOC estimator based on multi-state UKF has a better performance.

In order to further analyze the performance of presented method under extreme SOC conditions, the other set of experimental

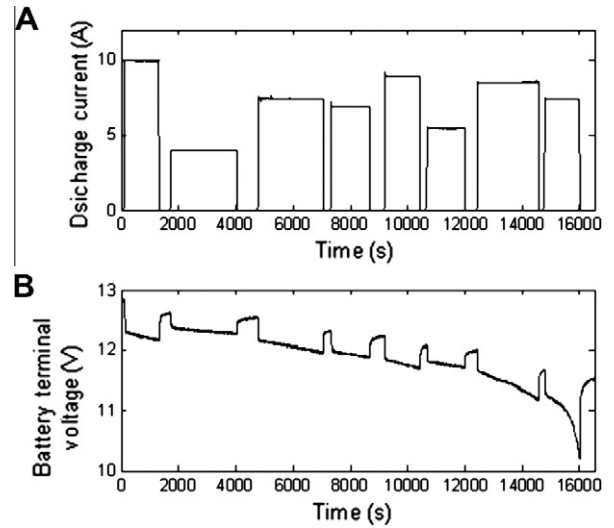


Fig. 7. Discharge current and battery terminal voltage under random current pulse discharge test.

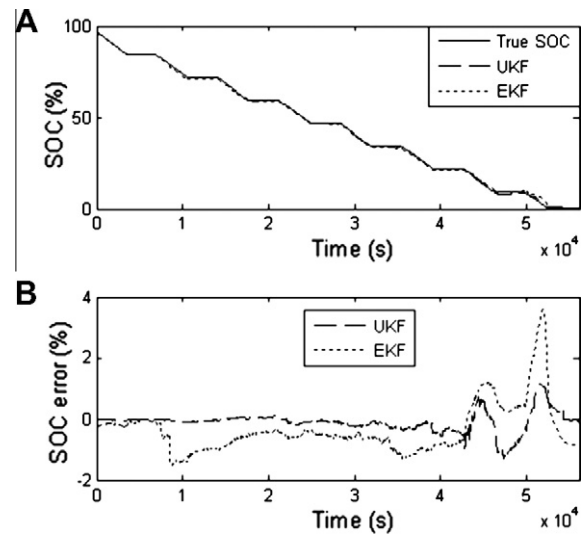


Fig. 8. Comparison of SOC curves under constant current pulse discharge test.

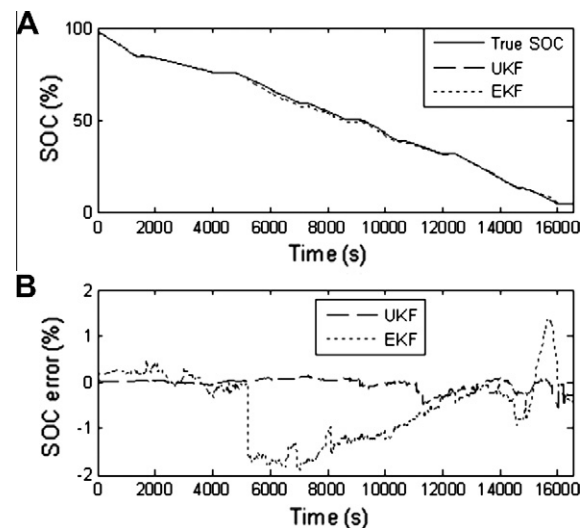


Fig. 9. Comparison of SOC curves under random current pulse discharge test.

tests are conducted. This time INT series 6FM40 VRLA battery is used, and its actual available capacity is around 32Ah. The experimental procedure is just similar to the previous one, major difference is that the SOC range being analyzed is greatly expanded. The discharge processes start with the battery almost full charged, and end when battery terminal voltage reaches its bottom limit 10 V. Fig. 6 shows the current and terminal voltage of a constant current pulse discharge test, Fig. 7 shows the current and terminal voltage of a random current pulse discharge test.

Comparisons of estimated SOC curves by EKF and presented UKF method are shown in Figs. 8 and 9.

It can be clearly seen from Figs. 8 and 9 that again the error caused by multi-state UKF method is much smaller, which means the presented UKF method is superior to EKF method in SOC estimation within almost the whole SOC range from 0% to 100%. Besides, the results also show that there is a noticeable error increase especially when the battery SOC is very low, this is mainly caused by the high nonlinear operating performance of the VRLA battery when it is near empty. In the two discharge processes as shown in Figs. 8 and 9, the maximum values of this error are 3.6% and 1.4% respectively by using EKF method, while this error is greatly restrained by the multi-state UKF method with its maximum values of only 1.2% and 0.5% respectively.

5. Conclusion

In this paper, a comprehensive battery model is established, and a multi-state UKF algorithm is employed to estimate the SOC of VRLA battery. Compared with commonly used simple models, the nonlinear operating performance of the battery could be tracked more correctly. So an excellent combination of EMF method and Ah counting method is realized to estimate the battery SOC.

Besides, analysis showed that the whole recurrence process and the estimated SOC result is also greatly influenced by the equivalent parameters in Thevenin model. Actually, a statistical parameter

identification strategy is adopted in EMF method, and the parameter values are dynamically selected according to the present SOC state, details of this part has presented in our another paper [12], so this is an extra advantage of our SOC estimator. We can predict that this multi-state UKF SOC estimation method has a wider development space in the future.

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